786 *Journal of Electrical Engineering & Technology Vol. 6, No. 6, pp. 786~792, 2011*
http://dx.doi.org/10.5370/JEET.2011.6.6.786

Optimal Capacitor Placement Considering Voltage-stability Margin with Hybrid Particle Swarm Optimization

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Abstract – The present paper presents an optimal capacitor placement (OCP) algorithm for voltage-stability enhancement. The OCP issue is represented using a mixed-integer problem and a highly nonlinear problem. The hybrid particle swarm optimization (HPSO) algorithm is proposed to solve the OCP problem. The HPSO algorithm combines the optimal power flow (OPF) with the primal-dual interior-point method (PDIPM) and ordinary PSO. It takes advantage of the global search ability of PSO and the very fast simulation running time of the OPF algorithm with PDIPM. In addition, OPF gives intelligence to PSO through the information provided by the dual variable of the OPF. Numerical results illustrate that the HPSO algorithm can improve the accuracy and reduce the simulation running time. Test results evaluated with the three-bus, New England 39-bus, and Korea Electric Power Corporation systems show the applicability of the proposed algorithm.

Keywords: Optimal capacitor placement, Particle swarm optimization, Optimal power flow, Optimal var planning, Steady-state voltage stability

1. Introduction

In modern power system operation and planning, voltage stability is one of the main concerns in the maintenance of system security [10, 17]. The Var planning or capacitor placement problem is one of the major issues for power system planning [12–13]. To achieve system security, many types of equipment have to be constructed; however, for reasons of economic efficiency, equipment construction has been limited. Therefore, finding the optimal location and amount of equipment that should be provided is crucial, which is a very difficult problem.

Optimal capacitor placement (OCP) problems contain integer variables because each capacitor bank has an integer value. Therefore, the problem being considered is a mixed-integer problem (MIP), as well as a highly nonlinear problem, because power systems are highly nonlinear. In the literature [2–5], several optimal power flow (OPF) algorithms using the interior point method (IPM) have been proposed. These algorithms can be adjusted to deal with the OCP problem. For the OCP problem, the bender's decomposition method [6] and the heuristic algorithm [1] can be applied for the consideration of contingencies. However, these algorithms present difficulties both in finding a solution to the MIP and in finding a global solution. In the literature [7], the tabu search algorithm, a local search algorithm, is applied for optimal Var planning. This algorithm deals well with the MIP; however, it does not always guarantee the discovery of the global optimal solution in a finite time. Generally, MIP provides a fast and reasonable solution that is suboptimal but nearly global optimal. In [18] and [19], artificial intelligence techniques such as simulated annealing, evolutionary algorithms, and artificial neural networks were used to overcome the difficulties of conventional OPFs. The particle swarm optimization (PSO) is a modern heuristic algorithm developed by Kennedy and Eberhart [8–9]. The advantages of PSO are its ease of implementation and adjustment of only few parameters. This method can easily identify a global solution and deal with integer variables [11–12, 14–16]. Therefore, this method is suitable for OCP. However, PSO has also some disadvantages: it is too slow for application to a large system and does not always converge to a single solution. The modified PSO (MPSO) is applied to overcome the defect of PSO. MPSO is a hybrid algorithm that combines PSO with local search techniques. It improves the probability of finding a global solution (i.e., the probability of convergence to one solution consistently). However, this approach requires more search time because the local search is too slow.

The present paper presents OCP considering the voltage stability enhancement. For MIP and highly nonlinear system, the hybrid PSO (HPSO) algorithm is adopted. The main algorithm is composed of IPM [10] and PSO [20]. To calculate the voltage stability margin (VSM), IPM is applied. Using the IPM results, the dual variable is applied to the velocity of PSO. At this point, the objective function of the IPM is the maximum loadability. To determine the

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Received: February 7, 2011; Accepted: June 23, 2011

optimal location and amount, PSO is applied. The dual variables perform the function of local search. This algorithm has a very fast simulation running time because IPM is very fast compared to a local search. At this point, the objective function of PSO is the minimum capacitor placement.

The remaining sections of this paper are organized as follows. Section 2 discusses the fundamental algorithm for the OCP problem by considering VSM when dealing with the introduced HPSO. Section 3 presents the numerical results and discussions. Finally, Section 4 provides conclusions.

2. Formulation and Solution Procedure of the OCP Problem

The objective function of OCP is a minimum capacitor placement cost and a guaranteed VSM. The voltage stability assessment may be calculated by means of a continuation power flow method or the OPF method. In the current paper, the voltage stability assessment is performed by OPF based on IPM. Through the OPF result acquisition, the dual variable information is adjusted to the velocity of PSO.

2.1 Formulation of the OPF Problem

The OPF module performs the maximum loadability. It searches the maximum transfer limit (PV margin) including the shunt amount offered by PSO. The objective function is given by the following equation:

$$\min \; f(x) = -\alpha \tag{1}$$

where α corresponds to a scaling factor of the loads.

The constraints of OPF include the network equation and inequality constraints that contain operational, physical, and old/new Shunt Capacitor/Reactor limits. The limits of the inequality constraints are as follows:

Upper/lower limits of bus voltage;
Upper/lower limits of reactive power generation;
Upper/lower limits of old/new SC/SR capacity; and
Upper/lower limits of active power generation (only with the slack bus).

Except for SC/SR, all constraints are normally used in optimal reactive power flow problems. The shunt capacitor constraints include the new shunt capacitor amount, which is offered by PSO.

The equality constraints can be expressed in the following form:

$$\begin{aligned} &P_{Ti} + \alpha P_{Li} - \alpha P_{Gi} = 0 \\ &Q_{Ti} + \alpha Q_{Li} - Q_{Gi} - B_i V_i^2 = 0 \end{aligned} \tag{2}$$

where the subscripts G, L, and T indicate generation, load, and injection, respectively, and V_i and B_i are the voltage and old/new shunt of bus i, respectively. The initial value of α is 1. The objective function (1) minimizes (-α) such that α is maximized.

The IPM algorithm is applied to the search solution. For IPM, the Lagrange function is given by the following:

$$\begin{aligned} L(\bullet) = f(x) - \lambda^T h(x) - z^T (g(x) - l - g_{\min}) \\ - w^T (g(x) + u - g_{\max}) - z^T l - w^T u \end{aligned} \tag{3}$$

where f, h, and g are objective function (1), equality constraints (2), and inequality constraints, respectively; λ, z, and w are dual variables; l and u are slack variables; and $g_{\min}$ and $g_{\max}$ are the upper/lower limits of the inequality constraints, respectively.

In (3), dual variables (λ) denote incremental cost, which is the incremental value of the objective function when the load is increased. The following equation describes the concept of λ :

$$\lambda_P = \frac{\partial f}{\partial P_L} \quad , \; \lambda_Q = \frac{\partial f}{\partial Q_L} \tag{4}$$

If the capacitor is allocated at bus i, the reactive load at bus i is decreased. Because the objective function is maximum loadability, (- λ_Q) represents the amount of increased loadability according to the allocated capacitor. If the maximum loadability is less than the desired margin, the capacitor is allocated at the bus that presents the largest (- λ_Q). Similarly, if the maximum loadability is greater than the desired margin and too many capacitors are allocated, the capacitor is removed at the bus that presents the lowest (- λ_Q). Therefore, λ_Q can be applied to a direction vector for capacitor allocation studies. However, the IPM algorithm searches for the local optimal solution; thus, λ_Q must be applied for the local optimal solution.

If OPF is used to calculate the maximum loadability, information regarding λ_Q can be obtained. Here, λ_Q represents how many capacitor banks are needed at any bus for a desired margin. This information can be applied to search for the local optimal solution in the form of a direction vector, and this algorithm is very fast.

2.2 Formulation of the PSO Problem

PSO is a modern heuristic algorithm. It can search for a global solution and handles integer variables easily. Therefore, PSO is useful for the application of the OCP problem. However, it does not converge to a unique solution (i.e., the answer varies with each performance). Therefore, to obtain a reasonable solution, the local optimal solution must be determined. In this section, the traditional PSO is introduced, and the HPSO algorithm is suggested.

The procedure for PSO is very simple.

Step 1: Generate the particle.

Each particle is generated by the random variables.

Step 2: Calculate the objective function.

Decide the global best and each individual local best.

Step 3: Calculate the velocity of each particle.

Step 4: Update solution of each particle.

Step 5: Return to Step 2 until all particles converge to one solution.

The procedure for operation of the suggested algorithm is the same as with an ordinary PSO algorithm. Only the velocity calculation method is different. For OCP, each particle contains information regarding the capacitor and the amount in each location. This amount is generated by the random variables. The objective function for OCP is given by the following:

$$\begin{aligned} &\min\ f = \left(\sum_{i=1}^{S} c_i(\cdot) B_i^{new}\right) - w\alpha \\ &if\ \alpha \le desired\ margin,\ then\ w = large\ value \\ &ortherwise,\ w = 1 \\ &c_i(\cdot) = cost\ function\ of\ B_i \\ &S \in candidate\ location\ set \end{aligned} \tag{5}$$

where B_i^{new} is the allocated capacitor amount at bus i, α is VSM (PV margin), and w is the weighting factor. OCP, considering VSM, has to satisfy the desired margin. Therefore, if VSM does not satisfy the desired margin or OPF does not converge because of the lack of the allocated capacitor, the weighting factor (w) has a very high cost.

After the calculation of the objective function, each particle updates each local best; the global solution is updated also. The velocity is then calculated to update each particle. The equation of the velocity is as follows:

$$\begin{aligned} v^t &= w \cdot v^{t-1} + C_1 \cdot r_1 (P_{best} - P_C) + C_2 \cdot r_2 (G_{best} - P_C) \\ &- C_3 \cdot r_3 \cdot \frac{\lambda_Q}{\lambda_Q^{average}} \cdot \frac{\alpha_{des} - \alpha_C}{\lambda_Q^{average} \cdot B_{size} \cdot s} \end{aligned} \tag{6}$$

where w is the inertia weight; r_1, r_2, and r_3 are random numbers between 0 and 1; P_{best} and G_{best} are the local best and global best, respectively; P_C is the current location of each particle; and C_1, C_2, and C_3 are positive constants known as the cognitive and social parameters (acceleration parameters). These acceleration factors pull the solution toward the P_{best} and G_{best} positions. Here, λ_Q and $\lambda_Q^{average}$ are the dual variables from the OPF and the average value of the dual variables, respectively; α_{des} and α_C are the desired VSM and the VSM of each particle, respectively; B_{size} is the shunt capacitor amount per one bank; and s is the total number of the candidate location.

The suggested algorithm uses the dual variables from the OPF result. Using (4), it can be rewritten in the following forms:

$$\lambda_Q = \frac{\partial f}{\partial Q_L} = -\frac{\partial \alpha}{\partial B_i} \tag{7}$$

$$\lambda_Q^{average} \cdot B_{size} \cdot s = -\frac{\partial \alpha}{\partial B_i} \cdot B_{size} \cdot s = \Delta\alpha \tag{8}$$

In (8), $\lambda_Q^{average} \cdot B_{size} \cdot s$ means $\Delta\alpha$ when one shunt capacitor bank is allocated at every location. Therefore, in (6), $\frac{\alpha_{des} - \alpha_C}{\lambda_Q^{average} \cdot B_{size} \cdot s}$ denotes how many shunt capacitor banks are needed at every location. In addition, in (6), $\frac{\lambda_Q}{\lambda_Q^{average}}$ pulls the solution toward the more sensitive buses. Therefore, $\frac{\lambda_Q}{\lambda_Q^{average}} \cdot \frac{\alpha_{des} - \alpha_C}{\lambda_Q^{average} \cdot B_{size} \cdot s}$ calculates the direction vector to allocate more capacitor banks to the more sensitive buses.

In (6), w is the inertia weight, which helps in the search for the local optimal solution. If the inertia weight is high, obtaining convergence to one solution is difficult. Therefore, the inertia weight has to be high at the first iteration and low at the nearby optimal solution. The inertia weight is given by the following relations:

$$w = 2w_1 + w_2 \tag{9}$$

$$w_1 = \frac{10 - iter}{20} \quad (iter \le 10,\ else\ iter = 10) \tag{10}$$

$$w_2 = \frac{1}{2} \cdot \frac{\sqrt{\sum (G_{best}^{iter} - P_C^{iter})^2}}{\sqrt{\sum (G_{best}^{1} - P_C^{1})^2}} \tag{11}$$

where "$iter$" is the iteration number that starts from zero; G_{best}^{iter} and G_{best}^{1} are the global best of each iteration and first iteration, respectively; and P_C^{iter} and P_C^{1} are the location of the particle at each iteration and first iteration, respectively. Here, w_1 is decreased at each iteration; however, if the global best is updated, "$iter$" is reset to zero. In contrast, w_2 is decreased as each particle is moved to the global best. Therefore, w is changed from 1.5 to nearly 0.

From (6), the position of the particle is updated:

$$P_C^{t+1} = P_C^{t} + v^{t+1} \tag{12}$$

2.3 Solution Procedure of OCP

OCP must consider the contingency. First, each particle is generated randomly. Then, the voltage stability assessment is performed by OPF. The single particle is performed according to the number of contingencies. The objective function is calculated through OPF and the allocated capacitor banks. The objective function of each particle has to be updated by the greatest value of all contingencies (i.e., the most severe contingency). After all contingencies are performed, each particle is updated according to the velocity of PSO. Fig. 1 shows the flowchart for overall procedure.

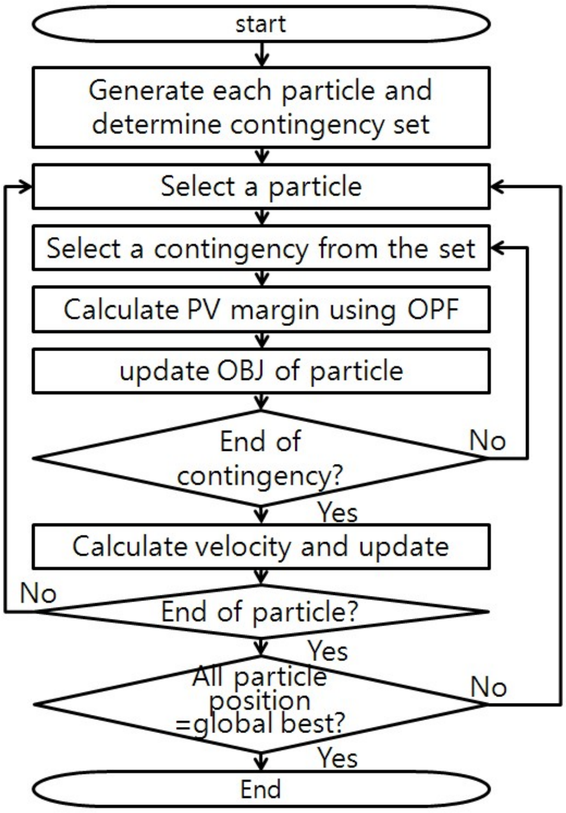

Fig. 1. Flowchart of the OCP procedure

3. Simulation Results

This section provides an example of an application of the proposed method, OCP, into the three-bus test system, the New England 39-bus test system, and Korea Electric Power Corporation (KEPCO) system, for verification. First, the three-bus test system is applied to show the principle of the suggested algorithm. Next, the New England 39-bus test and KEPCO systems are adopted to prove the superiority of the suggested algorithm. In the three-bus test system, the particle number is 3, the candidate location is all the load buses (two buses), and six banks (2 MVar per bank) can be allocated at every load bus. In the New England 39-bus test system, the particle number is 50, the candidate location is all the load buses, and five banks (10 MVar per bank) can be allocated at every load bus. In the KEPCO system, the particle number is 50, the candidate location is all the 154 kV load buses, and six banks (5 MVar per bank) can be allocated at every candidate bus. The desired VSM (α) is 1.1 in the case of the three-bus test system, 1.8 in the case of the New England 39-bus test system, and 1.05 in the case of the KEPCO system. The contingency is not considered to reduce the progress time. Each C_1, C_2, and C_3 is 1. FORTRAN is used as a front-end language, and the simulations are carried out on an Intel Core 2 CPU, 2.4 GHz, 2 GB RAM processor. All the suggested algorithms (OPF, PSO, and HPSO) were programmed by the authors.

Table 1. Topology and data for the three-bus test system

Bus data			
Num.	Type	Gen.	Load
1	Gen.	150 MW	-
2	Load	-	50 MW, 25 MVar
3	Load	-	100 MW, 40 MVar

Branch data		
From	To	X
1	2	0.1 p.u
1	3	0.5 p.u
2	3	0.5 p.u

Table 2. Process comparison of PSO and HPSO

Iteration Num.	1		2	
Bus Num.	2	3	2	3
Cap. Banks	4	6	1	6
Ran1	0.091	0.091	0.788	0.788
Ran2	0.97	0.97	0.17	0.17
Ran3	0.452	0.452	0.626	0.626
Pbest	4	6	1	6
Gbest-A	2	6	0	6
Lambda Q (a)	-0.423	-0.804	-0.443	-0.805
Average (b)	-0.614		-0.624	
Margin	1.134		1.113	
Delta a	-0.02456		-0.02496	
System needs	1.3844		0.5208	
(b)/(a)	1.452	0.764	1.409	0.775
PSO	2	6	1	6
HPSO	**1**	**6**	**0**	**6**

PSO is useful to solve the problem including integer variables and to search for a global solution. However, the algorithm is difficult to converge at the unique solution always; thus, improving the probability is crucial in order to search for a global solution. HPSO is suggested for accuracy. The proposed method offers a better direction vector using the dual variables of PSO based on experience. The two-bus test system shows searching process of the proposed method. The topology and complete data of the three-bus test system are given in Table 1. Table 2 shows one result from among many simulation cases. The four capacitor banks are allocated at Bus 2, and the six capacitor banks are allocated at Bus 3 denoted by 4, 6. The generated random numbers r_1, r_2, and r_3 are 0.091, 0.970, and 0.452, respectively. Currently, the global best is 2, 6. The values of λ_Q^1 and λ_Q^2 are -0.423 and -0.804, respectively. In 4, 6, VSM is 1.134 (>desired margin 1.1). This means that too many capacitor banks are located at this bus. In (8), when one capacitor bank is allocated at every location, VSM is reduced by 0.02456. $\frac{\alpha_{des}-\alpha_C}{\Delta\alpha}$ (=1.3844) means that the number of capacitor banks has to be reduced at each bus. Therefore, in (6), the next location of the particle is 1, 6. If ordinary PSO, is applied the next location of the particle is 2, 6. In this case, the global solution is 0, 6. Therefore, the faster and more accurate solution can be obtained from the proposed method.

Table 3. Objective function results for each case

		Objective function value			
		Average	Worst	Best	Std.dev.
Three-bus system	PSO	5.4735	9.8613	4.8943	0.9555
	HPSO	**5.0550**	**5.8967**	**4.8943**	**0.3664**
New England system	PSO	21.89	28.19	20.19	2.0518
	HPSO	**20.64**	**22.19**	**20.19**	**0.5895**
KEPCO system	PSO	572	1,566	246	381
	HPSO	**320**	**388**	**146**	**79**

Next, the effectiveness of the proposed method is verified. Case 1 is the ordinary PSO method and Case 2 is the proposed method (HPSO). Table 3 and Figs. 2–4 show the objective function results in Cases 1 and 2. For an accurate result, 50 simulations per case for the three-bus test system, 20 simulations per case for the New England 39-bus test system, and 10 simulations per case for the KEPCO system were performed. In Figs. 2–4, the two results are compared. The horizontal axis is the number of times the simulation was performed, and the vertical axis is the objective function value. The result of Case 1 is not uniform, that is, the possibility of finding the optimal solution is very low. The other side, Case 2, has higher possibility of finding the optimal solution. The standard deviation, average, and worst and best values of the final solutions of the different algorithms for Cases 1 and 2 are shown in Table 3. HPSO, combined with PSO and OPF based on IPM, obtains higher-quality solutions compared to the ordinary PSO algorithm. For all categories, including standard deviation, averages, and worst and best values, HPSO achieves lower values.

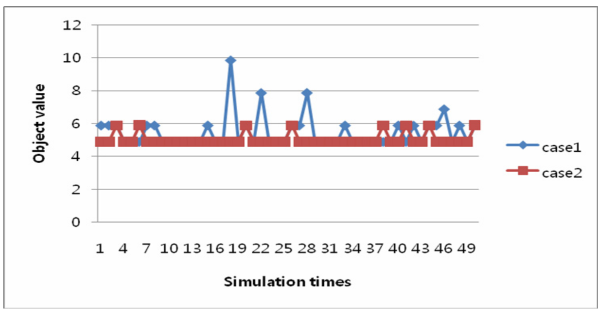

Fig. 2. Objective function results for the three-bus test system

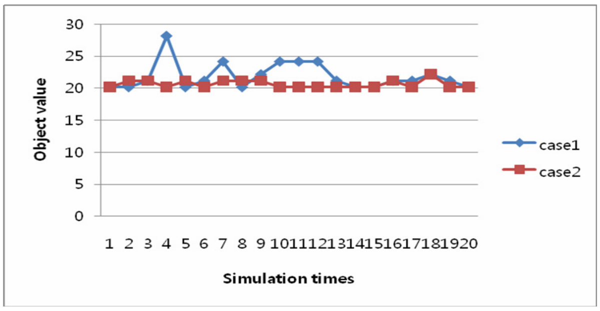

Fig. 3. Objective function results for the 39-bus test system

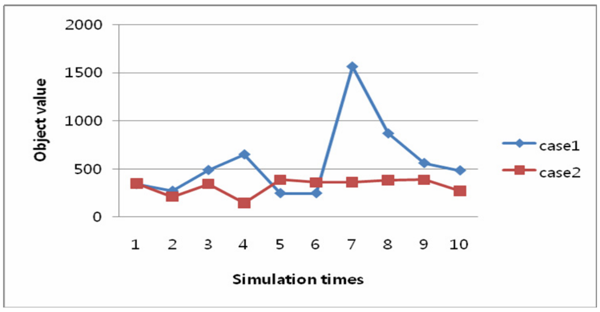

Fig. 4. Objective function results for the KEPCO system

Table 4 and Figs. 5 and 6 show the CPU times for Cases 1 and 2. The two results can be compared using Figs. 5 and 6. The horizontal axis is the number of times the simulation was performed, whereas the vertical axis is the CPU time (s). The result shows that CPU time for Case 2 is less than that for Case 1. The suggested algorithm reduces the CPU time by three times on average. In Table 4, for all categories, HPSO achieves faster simulation times.

Table 4. CPU times for each case

		CPU running times (s)			
		Average	Worst	Best	Std. dev.
New England system	PSO	583	809	280	129
	HPSO	**180**	**268**	**64**	**46**
KEPCO system	PSO	8275	13024	5004	2455
	HPSO	**5522**	**6516**	**4744**	**508**

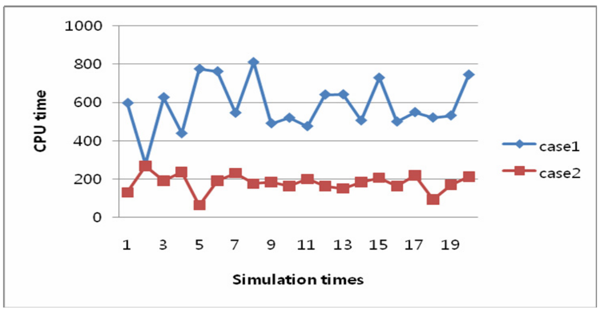

Fig. 5. CPU times for the New England 39-bus test system

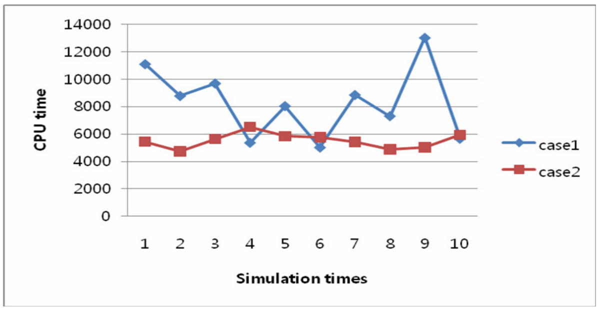

Fig. 6. CPU times for the KEPCO system

4. Conclusion

The present paper proposes OCP that considers VSM based on HPSO algorithm, which is useful for Var planning in the power systems. The power system planning must also consider VSM. The suggested algorithm is able to find the appropriate solution to ensure VSM. To solve the OCP problem, the PSO algorithm is applied because it is able to find a global solution and can easily handle the integer variables. The PSO algorithm has limitations in solving the optimal solution; thus, the suggested algorithm complements a weak point of PSO.

The present paper demonstrates the quality of the suggested algorithm through the test and KEPCO systems. The improved PSO shows good characteristics in terms of accuracy and simulation running time. However, it is too slow to apply to a large system. Studies for an algorithm with greater accuracy and faster running time have to be advanced.

Acknowledgements

This work was supported by grants from the Korea University and from the National Research Foundation of Korea (NRF) funded by the Korea government (MEST) (No. 2011-0017650).

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